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Workforce sleep and corporate innovation

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ABSTRACT

This study investigates the relationship between workforce sleep and corporate innovative output. Using comprehensive data on average sleep durations and corporate patenting, we present robust evidence demonstrating that aggregate sleep deficits among employees, engineers, and scientists are associated with declines in corporate patent output. The results further suggest that the decreases in output are greater for novel, breakthrough patents. Reductions in workforce sleep are also associated with declines in total factor productivity at high research-oriented firms. For identification, we apply a spatial regression discontinuity design and a novel natural experiment which induce exogenous changes in workforce sleep durations. Our findings are consistent with the notion that sleep has important value for efficiency and creativity in a firm's innovative process. This work highlights the importance of flexible work policies that allow employees to adjust their schedule to fit their own natural sleep cycle.

1. Introduction

Sufficient sleep is essential for maintaining and optimizing human capital, especially creativity (Opoku et al., 2023; Weinberger et al., 2018). Numerous studies from various fields have highlighted the correlation between sleep and individual performance in creative and complex tasks (Opoku et al., 2023; Sanders et al., 2019; Sio et al., 2013). Insufficient sleep has been linked to declines in cognitive function and memory, which can impede the ability to use existing information and generate innovative ideas. Even minor reductions in sleep can significantly impact employee creativity (Rosekind et al., 2010; Wagner et al., 2004). Additionally, another body of literature strongly connects creativity to innovative outcomes (Weinberger et al., 2018; Williamson et al., 2019).

Given the relationship between decreased sleep, reduced creativity and productivity, and the importance of creativity in driving innovation and technological progress, it is reasonable to hypothesize that the aggregate level of employee sleep within a firm could influence corporate innovation. However, research linking sleep to creativity, and creativity to innovation is typically constrained to laboratory studies (Gish et al., 2019; Sanders et al., 2019), due to data limitations.

In this study, we test whether these established relationships between sleep, creativity, and innovation in controlled settings also apply to the innovation output of corporations, using multiple identification strategies that capture exogenous changes in the aggregate sleep level of an area's workforce. We argue that a lack of sleep inhibits the idea generation process, which results in fewer innovations for the firm. In addition, a lack of sleep also influences the idea elaboration aspect of the process, further reducing the number of innovations produced by the firm.

To investigate the relationship between aggregate sleep declines and corporate innovation, we first leverage the discontinuity in sunset times across time zone boundaries to calculate the exogenous discontinuity in sleep, following other studies (Giuntella and Mazzonna, 2019). Using a wide set of demographic controls and geographic fixed effects, we find that being on the late sunset side of a time zone boundary is associated with an average decrease of about 30 min. In addition, we find that being on the late sunset side of the time zone boundary is associated with a decline in innovation of about 24 patents per year per firm. Our results are robust to several different tests. Overall, this suggests aggregate sleep declines can drive differences in corporate innovation.

Our study contributes to the literature in several ways. We contribute to a multilevel theory of innovation as well as the behavioral and microfoundations literature by investigating how lower-level, individual factors affect corporate-level innovation in various ways (Anderson et al., 2014). Prior studies were forced to ignore some of these lower-level antecedents due to a lack of available data and therefore relied on small-scale experiments conducted over a short period. Although the

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findings of these small-scale experiments are appropriate to study creativity, they are less ideal for corporate innovation, which often takes years to manifest. Second, we contribute to recent efforts developing an integrative theory of constraints on firm innovation (Acar et al., 2019) by highlighting sleep as an important constraint. Neurological constraints are scarce due to the difficulty linking individual level constraints to firm level outcomes. Third, our results relate to the literature on (micro)geography. Although, prior studies have established an important connection between geography and innovation (Roche, 2020), we link arbitrary and non-physical geographical barriers (i.e.. time zone borders) to corporate innovation.

To the best of our knowledge, this is the first study to relate declines in workforce sleep to changes in corporate innovative performance on a macro-scale, using a representative sample of US public firms. The findings illustrate that sleep deficits in employees have a measurable impact on firm innovation. If aggregate workforce sleep has a measurable and substantial impact on a firm's patent output, it underscores the value of implementing more flexible work arrangements that better accommodate and encourage individual natural circadian rhythms. Given the importance of innovation to the long-term survival of the firm (Aghion and Howitt, 1990; Hirshleifer et al., 2013; Schumpeter, 1934) and society (Solow, 1957), these findings carry significant implications for how innovative firms approach their employee policies and location choice strategies.

2. Background literature

2.1. Sleep and cognitive performance

The association between rigid work schedules and declines in sleep is part of a broader body of literature on "social jetlag," which refers to the mismatch between an individual's biological time, governed by their internal body clock, and the social times dictated by work schedules (Caliandro et al., 2021). Studies show that work schedules that either start later in the day or can be set by the employees themselves lead to healthy levels of sleep for employees (Geiger-Brown et al., 2011; Giuntella and Mazzonna, 2019).

The effects of insufficient sleep on individual cognitive performance are well documented. A lack of sleep leads to declines in productivity; for example, Gibson and Shrader (2018) apply sunset time as an instrument for sleep duration and find that sleep declines among employees reduce labor productivity. Even relatively modest declines in sleep can have sizable effects on cognition. In one study, after being restricted to five hours of sleep per night for four consecutive nights, subjects' cognitive performance was comparable to that from having a blood alcohol concentration close to the legal limit for driving (Elmenhorst et al., 2009).

Furthermore, Lanaj et al. (2014) find that sleep deprivation resulting from late-night smartphone usage leads to heightened depletion in individuals the next morning. In a study of 4188 employees at US corporations, Rosekind et al. (2010) find that workers with insufficient sleep had significantly worse productivity and performance. Ishibashi and Shimura (2020) find that workers who sleep less than five hours, and between five and six hours, are significantly less productive than those who sleep between seven and eight hours.

Regarding creativity, in a field study examining the effectiveness of entrepreneurs, researchers found that sleep has a distinct influence on the individual creativity of the entrepreneurs (Weinberger et al., 2018). The study finds that about 77 % of the daily variance in creativity is due to within-person fluctuations, of which sleep is a major component. The authors attribute this result to the import memory regulation that occurs during sleep. Research finds that during sleep, the cognitive processes of memory processing take place, which ultimately enhances the development of creative ideas (Amabile et al., 2005; Sio et al., 2013). This important process which aids in regulating creativity is interrupted and weakened in poor sleep states.

In summary, research indicates that workers are significantly less efficient and productive under conditions of even relatively mild sleep deficiencies, inhibiting creativity.

2.2. Creativity and innovation

Creativity has often been conceived as the generation of novel and useful ideas (Amabile and Pratt, 2016; van Knippenberg, 2017), whereas innovation has been argued to be the implementation of creativity, although some have used the term innovation to refer to the entire process (Oldham and Cummings, 1996; Shalley and Zhou, 2008). Scholars that refer to innovation as the entire process argue that creativity plays a crucial factor at each stage of the process, and that this iteration of creativity at every stage results in a recursive process of idea generation, elaboration, and implementation (King, 1992; Paulus, 2002; Van de Ven et al., 1989), with knowledge being a key component to creativity (Amabile, 1996).

Several studies have investigated the effects of individual level factors that constrain creativity (Acar et al., 2019). Constraints are defined as any externally imposed factor (e.g., rules and regulations, deadlines, requirements, and resource scarcity) that limits creativity and/or innovation (Acar et al., 2019, p. 98). These constraints can be at the input, process, or output level (Hülsheger et al., 2009; West and Anderson, 1996). Input constraints refer to the unavailability or resources such as time and human capital. Process constraints refer to the restrictions regarding the steps to be followed, whereas output constraints focus on factors that define the end results of the creative processes. In this study, we focus on a specific type of input constraint, sleep deprivation, that connects an individual level constraint to corporate level innovation.

Prior research focusing on input constraints has investigated the effects of personality traits (Baer and Oldham, 2006), regulatory focus (Sacramento et al., 2013), novelty-seeking tendency (Scopelliti et al., 2014), experience (Sellier and Dahl, 2011), job satisfaction, mood states (Amabile et al., 2005; Binnewies and Wörnlein, 2011; Fong, 2006; George and Zhou, 2007), and feelings of vitality and energy (Atwater and Carmeli, 2009; Kark and Carmeli, 2009), often with mixed results and at different levels of analysis. In essence, innovation is a process involving several steps (Perry-Smith and Mannucci, 2017) that produces an output with different degrees of success, depending on the constraints influencing this process (Acar et al., 2019). As such, we investigate a particular individual level input constraint, sleep.

3. Theory development

We conceptualize the innovation process occurring in several steps, starting with idea generation. Once an idea is generated it needs to be elaborated on to further develop this process after which the idea can be implemented, patented, or commercialized (Perry-Smith and Mannucci, 2017). However, this process is not necessarily linear. There can be several back-and-forth between the generation and elaboration phases in an iterative process that further develops the idea, increasing the likelihood of successful completion (Harvey, 2014). This entire process, however, is subject to constraints (Acar et al., 2019), including sleep. Fig. 1 depicts the innovation process along with our focal constraint of interest, and it previews our proposed hypotheses.

Several individual level factors influence the innovation process, including cognitive processes (Scopelliti et al., 2014). Cognitive processes refer to the process of creativity and innovation (e.g., cognitive fixation, cognitive search strategies, opportunity identification) that relate to accessing, searching for, and attending to information and transforming and recombining that information to generate creative an innovative outcomes (Acar et al., 2019). Therefore, factors that influence these cognitive processes are constraints on the innovation process.

A large literature of sleep medicine and management suggest that the cognitive declines from sleep loss are most likely to affect an individual's performance on complex and creative tasks (Opoku et al., 2023;

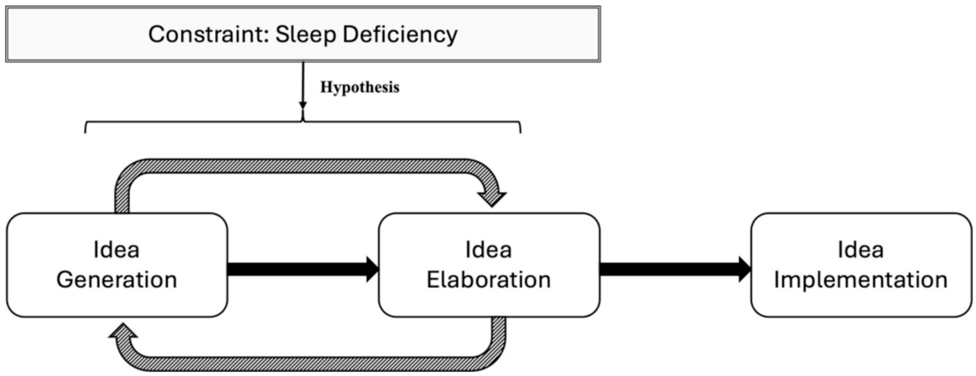

Fig. 1. Hypothesis Development. This figure charts the main hypothesis of this study. We present a model of an innovative process with sleep deficiency acting as a constraint.

Rosekind et al., 2010; Sanders et al., 2019; Sio et al., 2013; Wagner et al., 2004; Weinberger et al., 2018; Williamson et al., 2019). Creativity requires focus, cognition, and memory processing, all of which are complex by nature and are disrupted under conditions of poor sleep (Wagner et al., 2004; Williamson et al., 2019). Therefore, we argue that because a lack of sleep influences creativity, it is an important input constraint affecting the entire innovation process.

We argue that a lack of sleep is associated with a reduction in the number of innovations produced by the firm. The first step of the innovation process is idea generation, the process of generating a novel and useful idea (Perry-Smith and Mannucci, 2017). During this phase, many different ideas are generated out of which an idea or group of ideas are chosen. This selection can be preceded by a brainstorming process (Sutton and Hargadon, 1996), but differs from brainstorming as a single or group of ideas are selected that are deemed the most appropriate candidates for success. At this stage, the idea is still vague and needs to be elaborated on in the next steps of the process.

Clearly, the quality of the idea selected for further elaboration is dependent on the quality of the alternative ideas generated. Generating different ideas requires the ability to freely associate and connected disparate concepts, a process which often seems random and serendipitous (Zhong et al., 2008). Sleep deprivation has been found to reduce the ability to find relationships and linkages between seemingly unrelated concepts (Cai et al., 2009).

Another critical requisite is the ability to be open-minded to disparate ideas (Amabile, 1988). Even if novel ideas were to be generated, cognitive rigid thinkers and evaluators will be unable to properly evaluate the value of an idea (Amabile, 1996). In contrast, the more cognitive flexible evaluator will be better able to recognize and evaluate the novelty and importance of recombining conceptually different ideas (Simonton, 2003), a key part to the process of innovation (Fleming, 2001; Xiao et al., 2022). Research has found that a lack of sleep negatively affects this cognitive flexibility (Sio and Ormerod, 2009). This reduces the chances that a novel idea, worthy of elaboration and eventually successful patenting will be generated.

Once an idea is generated and selected, a second key step in the process is idea elaboration phase (Perry-Smith and Mannucci, 2017). During this phase the idea is scrutinized and systematically evaluated to a stricter degree in order to assess the idea's potential and identify areas for clarification. At this stage, cognitive flexibility is needed to identify inconsistencies and make improvements, improvements that are often novel on their own, requiring additional creative processes (Hargadon and Bechky, 2006). In addition, this process requires a certain level of comfort with uncertainty (Staw, 1990). This requires mental and emotional resilience (Madjar et al., 2002), both of which are reduced by a lack of sleep (Binnewies and Wörnlein, 2011; Fong, 2006). This could lead to the abandonment of novel ideas, especially those very novel ideas that often look like bad ideas initially (Harvey, 2014) and that require mentally strong champions.

Additionally, the more cognitive strength and flexibility the innovators possess, the more likely they can withstand critiques and come up with creative solutions to the problems uncovered or brought forth during the elaboration process. This results in an iterative process that increases the chances of countering critiques that increase the chances of success (Harvey, 2014). The stronger the cognition the more likely the innovator is willing to go through multiple iterative processes, to turn these initially "bad-looking" ideas into successful innovations.

Furthermore, knowing that sleep declines impact processes that require more complexity and individual problem-solving skills (Opoku et al., 2023; Rosekind et al., 2010; Sanders et al., 2019; Sio et al., 2013; Wagner et al., 2004; Weinberger et al., 2018; Williamson et al., 2019), this will reduce the number of times an idea goes through an iterative process and increases the likelihood an idea will be forsaken.

In summary, given the negative effects of sleep deprivation on the ability to generate novel ideas and recognize their value in the early stages of the innovation process, sleep deprivation will result in fewer ideas being generated. In addition, elaborating on an initial idea is a rigorous process that requires a significant amount of productivity on the part of the employees. This process increases the chances of successfully turning the idea into an innovation. Therefore, declines in sleep are associated with lower individual creativity and productivity, a lack of sleep can significantly impact the elaboration process. The combined effects of reduced idea generation and elaboration result in reduced corporate innovation. More formally:

Hypothesis. Sleep deficiency is negatively associated with corporate innovation.

4. Methodology

4.1. Data and sample

We first use data from the Census American Time Use Survey (ATUS). The purpose of this first dataset is to estimate the initial discontinuity in sleep duration. The survey has been conducted by the U.S. Bureau of Labor Statistics (BLS) since 2003. The ATUS sample is drawn from the recent sample of Current Population Survey (CPS) participants; as such, detailed information on demographic, economic, and occupational characteristics is recorded. To complete the survey, respondents complete a detailed time-use diary for the previous day. This includes information on time spent sleeping and a wealth of other activities.[1]

For the main dataset, we combine data from several sources. The United States Patent and Trademark Office (USPTO) provides data on the total number of patents.[2] We match firms to patent assignees in the USPTO using the match provided by the Kogan et al. (2017) dataset. We obtain firm-year accounting data from Compustat and stock market data from the Center for Research in Securities Prices (CRSP). We also include data on Total Factor Productivity (*TFP*) from Imrohoroğlu and Tüzel (2014).

After merging the data from the aforementioned sources, we restrict the analysis to firm-year observations with at least one granted patent. Following Kogan et al. (2017), we drop firms in financial industries (SIC 6000–6799), utilities (SIC 4900–4949), public administration and non-classifiable business (SIC >9000), and firms with missing book asset value. Overall, the sample consists of 11,234 firm-year observations from 2003 to 2017.[3]

4.2. Variables

From the ATUS data, we measure several key variables related to sleep. We apply these variables to illustrate the effects of time zone boundaries on sleep in the areas where the treated firms are located. First, we measure *Late Bedtime* as a variable equal to one if the respondent reports going to sleep after 11 p.m. In addition, we define *Early Wake Time* as a variable equal to one if the respondent reports waking before 7:30 a.m. The main dependent variable of interest in this first analysis is *Sleep Duration*, which we define as the total duration in minutes that the respondent spent sleeping during the previous night. To account for possible confounding effects related to demographic or economic characteristics, we include control variables for the respondent's marital status (*Married*), gender (*Male*), number of children (*Children*), educational attainment (*College*), age (*Age*), and annual income (*Income*).

Our main dependent variable to test our proposed hypothesis is *Patent Counts.* This variable corresponds to the number of patents a given firm applies for in a given year. In the main specification, we operationalize this measure as ln*(1 + Patents)*, which is the log-transformed total number of firm-year patents.[4] To account for possible confounding firm-level characteristics, we include a wide set of control variables. *ln (Total Assets)* is defined as the log-transformed total asset value of the firm. *R&D Intensity* is defined as the firm's total R&D investment divided by total assets. *ln(Employees)* captures the total number of individuals employed by the firm. *Leverage* is the sum of current liabilities and long-term debt divided by market equity. *Market-to-Book* is the market equity divided by the book equity, and *ROA* is net income divided by book asset value. Table 1 presents the summary statistics of the firm-year panel and Table 2 presents the pairwise correlations for the main variables we use in this study.

We discuss the main explanatory variables as part of the main empirical design in the following section. Table A1 in the appendix provides an overview of all our used variables, including those used in post-hoc analyses.

4.3. Empirical strategy

The primary design we apply is a spatial regression discontinuity design (RDD) (Imbens and Lemieux, 2008) leveraging the discontinuity in the timing of natural light around time zone boundaries (Keele and Titiunik, 2015) to test for the effects of insufficient sleep in a workforce. This empirical design has been used in various literatures, including strategy (Pongeluppe, 2022) and the literature on aggregate sleep loss and productivity (Gibson and Shrader, 2018). We also apply an additional triple-difference design as an alternative specification in Section 5.3.

For the primary spatial RDD, we exploit the discontinuity in sunset times across time zone boundaries to estimate principal effect on sleep. Given there are three time zone boundaries in the contiguous US (see Fig. 2), a standard regression discontinuity approach would compare individuals living on opposite sides of different time zone boundaries (such as comparing individuals residing in California and Florida). Additionally, the standard approach would compare individuals who live at different latitudes and thus have different sunset times. This necessitates the use of geographic fixed effects, in which we apply variations of state and latitude fixed effects. In the main empirical design, we use a battery of fixed effects, applying state × year, and industry × year, and latitude fixed effects. This implies that we are comparing the innovation of firms on different sides of the threshold, within the same state-year, within the same industry-year, and at the same latitude (1-degree bands). We exclude a 20-mile bandwidth on either side of the time zone boundary to account for any confounding effects of individuals who may live on one side of the threshold and commute to the other (we denote this as *Commuting Zone*).[5] Following Giuntella and Mazzonna (2019), we apply the spatial regression discontinuity design according to the following specification for the main analyses in Tables 3 and 4:

$$\mathrm{Y_{i,t}} = \alpha_0 + \alpha_1 \mathrm{LS_c} + \alpha_2 \mathrm{f(D_C)} + \alpha_3 \left(\mathrm{LS_{i,c}} \times \mathrm{f(D_C)}\right) + \alpha_4 \mathrm{X_{i,t}} + \alpha_5 \mathrm{W_{i,t}} + \alpha_6 \mathrm{Z_c} + \varepsilon_{\mathrm{i,t,c}} \tag{1}$$

where $Y_{i,t}$ is an outcome of interest, LS_c is an indicator for a county being on the late sunset side of a time zone boundary, and $f(D_C)$ is the distance to the time zone boundary in miles.[6] $X_{i,t}$ is a vector of control variables. $W_{i,t}$and Z_c are vectors of both industry × year and geographic fixed effects. In this specification, *c* indexes counties, *t* indexes time, and *i* indexes firms.

As with other spatial RDDs, the identifying assumption is that there are no other discontinuities in observable or unobservable characteristics across time zone boundaries that may confound the main results. Other studies have shown no discontinuities in demographic characteristics across time zone boundaries (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019). Although spatial RDDs already address endogeneity concerns to a certain degree, we als use an alternative specification where we apply a triple-difference design that leverages exogenous changes in the timing of natural light in the evening in Indiana to further address endogeneity concerns. We find very similar results as the initial design, and the aforementioned specification applies firm fixed effects, removing most selection concerns altogether (See Section 5.3).

Other studies apply similar techniques, namely leveraging discontinuities in time zone boundaries, to explore the effects of sleep loss on other outcomes. A number of such studies examine the effects of sleep

[1] To clean the data to avoid possible confounding demographic effects, we follow the procedure of Giuntella and Mazzonna (2019). We limit the sample to individuals who sleep between 2 and 16 h per night. We also focus on sleep starting and ending times between 7 a.m. and 7 p.m. Additionally, we restrict the sample to individuals aged between 18 and 55 to avoid any potential confounding effects of individual retirement. The final sample consists of 38,389 observations between matching the sample period of the main dataset (2003–2017).

[2] We collect the patent data from the PatentsView website. See: https://www.patentsview. org/download/.

[3] We begin the sample in 2003 in order to match the period in which county-level sleep patterns are observable in the ATUS.

[4] We also conduct Poisson specifications as an alternative to using the log-transformed patent measure. See Section 5.2.5.

[5] We illustrate the main results are robust to the application on a variety of bandwidth sizes of the *Commuting Zone* sample.

[6] Distance to the county centroid is the forcing (running) variable. We also refer to this variable as *Miles to TZ Border*.

Table 1
Summary Statistics.

	Mean	SD	25th	Median	75th
Panel A: Time Zone Variables					
LS	0.623	0.485	0	1	1
Miles to TZ Border	79.833	266.385	−116.745	76.870	253.445
Panel B: Sleep-Related Variables					
Late Bedtime	0.450	0.498	0	0	1
Early Wake Time	0.635	0.482	0	1	1
Sleep Duration	470.218	122.828	410	480	540
Married	0.535	0.499	0	1	1
Male	0.442	0.497	0	0	1
Children	0.884	1.287	0	1	2
College	0.395	0.489	0	0	1
Age	38.630	9.979	31	39	47
Income	94,468.814	66,569.345	46,100	76,923	125,000
Panel C: Patents and Firm Characteristics					
Total Patents	46.077	174.061	2	5	20
ln(Total Assets)	6.540	2.147	5.036	6.598	7.959
R&D Intensity	0.094	0.152	0.002	0.036	0.117
ln(R&D Spending)	2.429	2.030	0.374	2.337	3.817
Employees	9.861	37.050	0.215	1.085	5.400
Leverage	0.849	2.303	0.026	0.402	1.062
Market-to-Book	3.042	5.166	1.146	1.899	3.451
ROA	−0.043	0.257	−0.028	0.017	0.062
Cash-to-Asset	0.140	0.179	0.021	0.071	0.185
Destabilizing Patent Counts	31.146	130.923	1	3	11
Consolidating Patent Counts	6.705	26.756	0	1	3
TFP	−0.350	0.549	−0.578	−0.329	−0.079

This table reports the summary statistics for the key variables used in the analysis. Panel A summaries variables related to time zone boundaries, which are calculated using US county centroids. Variables in Panel B are sourced from the American Time Use Survey. Variables in Panel C are sourced from Compustat.

Table 2
Correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) LS (Late Sunset)	1.000								
(2) ln(1 + Patents)	−0.021	1.000							
(3) ln(Total Assets)	0.044	0.540	1.000						
(4) R&D Intensity	−0.157	−0.108	−0.359	1.000					
(5) ln(Employees)	0.074	0.495	0.693	−0.317	1.000				
(6) Leverage	0.049	0.028	0.158	−0.119	0.073	1.000			
(7) Market-to-Book	−0.044	0.035	−0.073	0.137	−0.005	0.343	1.000		
(8) ROA	0.069	0.163	0.360	−0.662	0.253	0.049	−0.059	1.000	
(9) Cash-to-Asset	−0.113	−0.075	−0.311	0.429	−0.225	−0.156	0.198	−0.296	1.000

This table reports the pairwise correlation matrix for the key variables of this study. The independent variable of interest in the main analysis is *LS*, an indicator variable equal to one if the firm headquarters are located on the late sunset side of a time zone border. The main dependent variable is the logarithm of one plus the number of total patents. Controls include *ln(Total Assets)*, *R&D Intensity*, *ln(Employees)*, *Leverage*, *Market-to-book*, *ROA*, and *Cash-to-asset*.

loss on labor productivity, which we explore our post-hoc analyses, given the relative task-complexity and sophistication of innovative thinking and activities (Gibson and Shrader, 2018). An additional study applies this identification strategy and finds that sleep loss declines lead to differences in long-term health outcomes, such as obesity, diabetes, cardiovascular diseases, and certain types of cancer (breast, colorectal, and prostate) (Giuntella and Mazzonna, 2019). It may be the case that these or similar health effects may be an alternative mechanism by which sleep loss impacts firm innovation, along with declines in labor productivity. We hypothesize that this is likely not the case, given that in the triple differences design, we observe changes in innovation relatively soon after Indiana adopted daylight savings time, whereas it takes a number of years for a condition like cancer to develop, suggesting labor productivity to be the primary mechanism.[7]

5. Time zones and sleep

This section measures the discontinuity in sleep duration related to the associated discontinuity in the timing of natural light around time zone boundaries to verify our proxy for aggregate sleep declines, following a set of other studies (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019). We plot the discontinuities in bedtimes and sleep duration in Fig. 3, panels A and B, respectively. Visually, in each case, following the literature, a significant discontinuity is observed.

We present the regression results of the spatial RDD estimating the effects of the timing of natural light on bedtimes, wake times, and sleep duration in Table 3. We apply the specification to two samples: one with individuals of all occupations and one with individuals of only engineering and scientific occupations. The former are uniquely important to the innovation process, and also routinely receive less sleep, which we plot in Fig. IA.1 in the Internet Appendix. Each model includes a wide set of demographic controls and state, time, and occupation fixed effects.[8]

[7] See: https://news.cancerresearchuk.org/2018/10/18/science-surgery-how-quickly-do-tumours-develop/

[8] In addition, we exclude the 20-mile commuting zone in columns 1–2, 4, and 6.

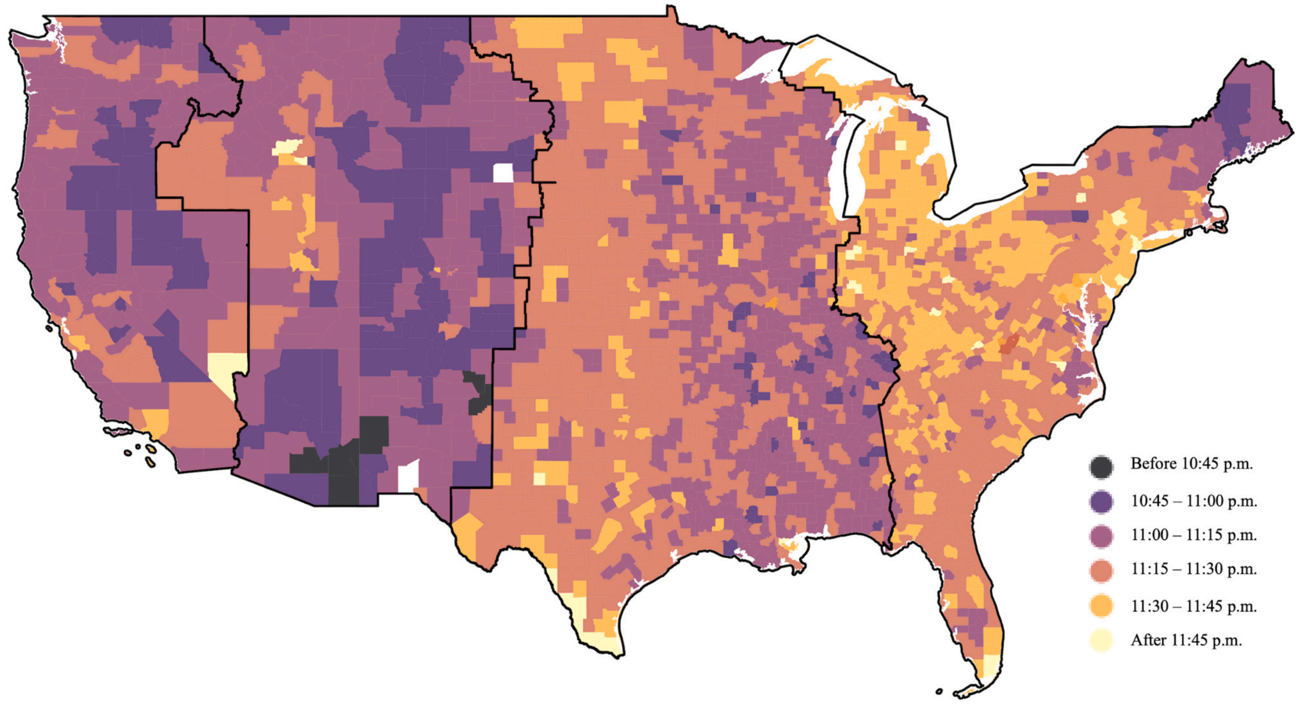

Fig. 2. Time Zones and Behavior. This figure reports the average bedtime by county in the contiguous United States. The data is sourced from the *Jawbone sleep tracker website* following Giuntella and Mazzonna (2019). Brighter colors indicate later bedtimes. US time zone boundaries are overlaid.

Table 3
Sunset Time and Sleep Duration.

	All Occupations				Engineering and Scientific	
	(1)	(2)	(3)	(4)	(5)	(6)
	Late Bedtime	Early Wake Time	Sleep Duration	Sleep Duration	Sleep Duration	Sleep Duration
LS	0.167***	−0.020	−29.941***	−29.376***	−32.982**	−40.843**
	(4.108)	(−0.501)	(−5.627)	(5.558)	(−2.066)	(−2.601)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	No	Yes	No	Yes
Observations	12,891	12,891	13,262	12,891	2511	2443
R-squared	0.055	0.122	0.045	0.046	0.071	0.071

This table reports the effect of a late sunset time on sleep duration. In Column 1, the dependent variable is *Late Bedtime*, an indicator variable that equals one if the respondent reports going to bed after 11 p.m. In Column 2, the dependent variable is *Early Wake Time*, an indicator variable that equals one if the respondent reports waking before 7:30 a.m. In Columns 3–6, the dependent variable is *Sleep Duration*, equal to the total amount of time in minutes the respondent spent sleeping on the reference day. The independent variable of interest is *LS*, an indicator variable equal to one if the respondent lives on the late sunset side of a time zone border. Engineering and scientific occupations (Columns 5–6) are defined as whether an individual belongs has a Census occupation code corresponding to computer and mathematical science; architecture and engineering; life, physical, and social science; or healthcare practitioner and technical occupations. Controls include *Married*, *Gender*, *College*, *Age*, and *ln(Income)*. All estimates include *Miles to TZ Border* and *LS · Miles to TZ Border*. *Commuting Zone* indicates whether observations from 20 miles on either side of the time zone boundary are excluded from the analysis. Weekends are excluded. Fixed effects are included where indicated. The spatial RDD bandwidth is 400 miles on either side of the time zone boundary. Key variables are defined in the Appendix. We winsorize all continuous variables at the 99 % level. Standard errors are clustered at the geographic level based on the distance to the time zone boundary. T-statistics are shown in parentheses. ***, **, * denote significance at 1 %, 5 %, and 10 % levels, respectively.

We test the effect of being on the late sunset side of the time zone boundary on bedtime and waking time in Column 1 and 2. We find that bedtimes are a function of solar cues, such that being on the late sunset side of the time zone boundary increases the probability of going to bed after 11 p.m. by 0.167 percentage points, which amounts to an increase of about 33 % the standard deviation of *Late Bedtime*.[9] Consistent with prior findings, we find that waking times are unaffected, with no statistically significant effect. Intuitively, this leads to an overall decrease in sleep duration, which we estimate in Columns 3–6. We estimate the sleep declines associated with being on the late sunset side of the time zone boundary are about 29.37 min of sleep per night for all occupations, representing declines between about 23 % the standard

[9] This estimate is also equivalent to about 40 % the mean of *Late Bedtime*.

Table 4
Aggregate Sleep and Innovation.

	(1)	(2)	(3)
DV: ln(1 + Patents)			
LS	−1.016**	−0.898***	−0.751**
	(−2.601)	(−3.288)	(−2.442)
Controls	No	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	No	Yes	Yes
Latitude FE	Yes	Yes	Yes
Commuting Zone	Yes	No	Yes
Observations	9374	7141	7037
R-squared	0.110	0.701	0.702

This table reports the effect of a late sunset time on innovation. The dependent variable is the logarithm of one plus the number of patents. The independent variable of interest is *LS*, an indicator variable equal to one if the firm headquarters are located on the late sunset side of a time zone border. Controls include *ln(Total Assets)*, *R&D Intensity*, *ln(Employees)*, *Leverage*, *Market-to-book*, *ROA*, and *Cash-to-asset.* All estimates include *Miles to TZ Border* and *LS* · *Miles to TZ Border*. *Commuting Zone* indicates whether observations from 20 miles on either side of the time zone boundary are excluded from the analysis. Fixed effects are included where indicated. The spatial RDD bandwidth is 400 miles on either side of the time zone boundary. Key variables are defined in the Appendix. We winsorize all continuous variables at the 99 % level. Standard errors are clustered at the geographic level based on the distance to the time zone boundary. T-statistics are shown in parentheses. ***, **, * denote significance at 1 %, 5 %, and 10 % levels, respectively.

deviation of *Sleep Duration* (6 % relative to the mean).[10] In Column 5–6, we isolate the sample to only those who are in an engineering and scientific professions, and find that being on the late sunset side of the boundary is associated with declines of about 40.84 min. In this way, we are able to empirically show that, in the counties where certain firms are located, the occupations typically associated with patenting see significant declines in sleep.

Overall, in this section, we illustrate how time zone boundaries create an exogenous disruption to sleep duration: A later sunset time on the eastern side of the time zone boundary leads to more individuals delaying sleep time, leading to less sleep. These findings justify our use of miles to the time zone border as a proxy for sleep deficiency.

6. Aggregate sleep and innovation

6.1. Main specification

This section tests our main hypothesis and applies the previous estimated discontinuity in sleep duration around time zone boundaries to estimate the effects of aggregate declines in sleep on corporate innovation. Following the previous section, we plot the discontinuities in our measures of innovation in Fig. 4. Mirroring the discontinuities in bedtimes and sleep duration from the previous section, we find a similar discontinuity in patenting. This figure provides some illustrative evidence that exogenous discontinuity in sleep duration impacts firm innovation.

Table 4 presents the main analysis. We apply a robust set of fixed effects, including state × year, and industry × year, and latitude fixed effects.[11] As such, we are both comparing firms in the same industry, in

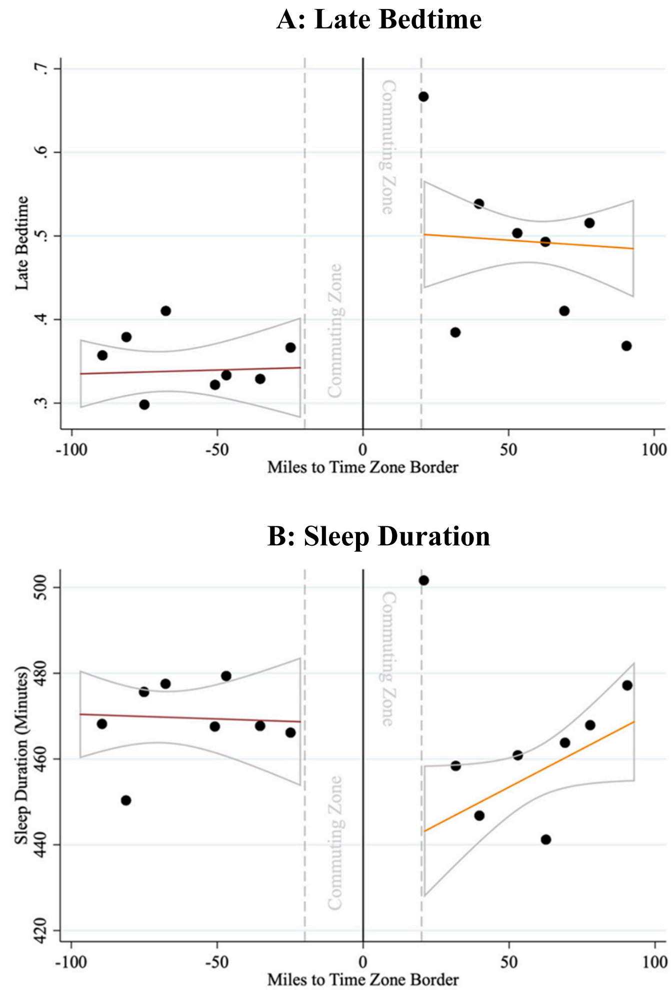

Fig. 3. Sleep-Related Discontinuities. Panel A: Late Bedtime. Panel B: Sleep Duration. This figure presents discontinuities related to bedtime and sleep duration across time zone boundaries. Each point represents a binned average value related to the variable of interest. The x-axis presents the running variable *Miles to TZ Border*, whereby positive values fall on the late sunset side of a time zone boundary and negative values fall on the early sunset side. A commuting zone, denoted in gray, represents excluded values within 20 miles of the time zone boundary. Fitted lines and the associated 95 % confidence intervals are shown on either side of the time zone boundary. Panel A reports average values of *Late Bedtime* relative to the time zone boundary threshold. *Late Bedtime* is an indicator equal to one if an individual reports a bedtime after 11 p.m. Panel B reports average values of *Sleep Duration* relative to the time zone boundary. *Sleep Duration* is equal to the total amount of time in minutes the respondent spent sleeping on the reference day.

the same state, on different sides of a time zone boundary. The results are robust to including or excluding the *Commuting Zone.*[12] Overall, the coefficients on *LS* are statistically significant in all models. The baseline specification is presented in Column 3.[13] For the average firm, being on the late sunset side of the time zone boundary is associated with a

[10] These results are consistent with those found in other studies, as Giuntella and Mazzonna (2019) find discontinuities in sleep duration between 19 and 36 min.

[11] We also illustrate our results are robust to an even larger set of alternative fixed effects in Table IA.1 in the Internet Appendix.

[12] Additionally, our results are robust to a variety of sizes of the Commuting Zone measure up to large bandwidths, which we illustrate in Figure IA.2 in the Internet Appendix.

[13] We cluster standard errors at the level of the running variable (Giuntella and Mazzonna, 2019). However, we illustrate our results are robust to a variety of clustering strategies in Figure IA.3 in the Internet Appendix.

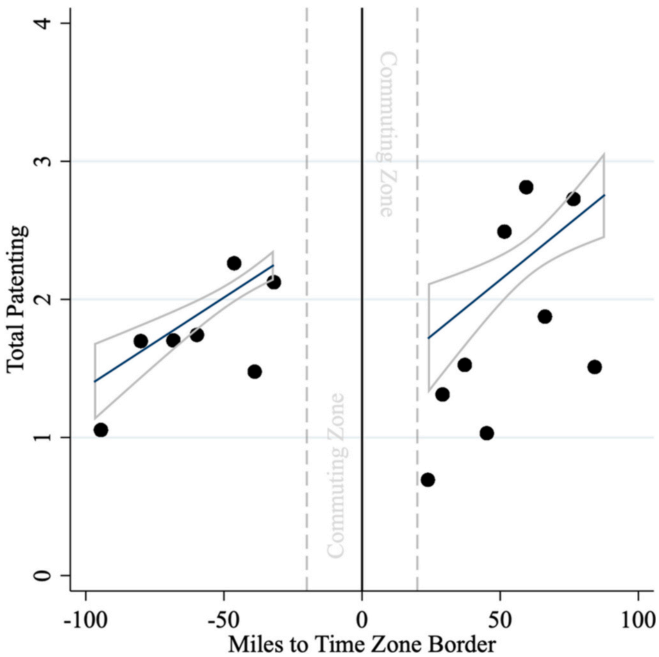

Fig. 4. Discontinuities in Innovation. This figure presents discontinuities related to innovation across time zone boundaries. Each point represents a binned average value related to the variable of interest. The x-axis presents the running variable *Miles to TZ Border*, whereby positive values fall on the late sunset side of a time zone boundary and negative values fall on the early sunset side. A commuting zone, denoted in gray, represents excluded values within 20 miles of the time zone boundary. Fitted lines and the associated 95 % confidence intervals are shown on either side of the time zone boundary. The figure reports average values of total patenting (ln(*1* + *Patents*)) relative to the time zone boundary threshold.

decrease of about 24 patents, which is about 13.7 % decrease in innovation relative to the standard deviation.[14] In summary, the results from the baseline analysis in Tables 4 suggest that sleep declines have a distinct and economically significant effect on firm innovation. In further sections, we apply a number of validating tests to verify the robustness of the results.[15]

6.2. Robustness

6.2.1. Firm characteristics

This subsection tests for differences in R&D spending and other firm characteristics on either side of the time zone boundary. This acts as a placebo test to aid identification; aggregate sleep declines empirically and theoretically lead to changes in total innovation output due to the relationships between sleep, efficiency, and creativity, but aggregate sleep declines should have no clear influence on a firm's policy as it relates to spending on research and development. Similarly, it should have little to no effect on firm fundamentals which are less related to innovation outcomes. We illustrate the results from this analysis in Table 5.

First, we test the effect of being on the late sunset side of the time zone boundary on *R&D Intensity*, which is the ratio of R&D spending to total assets. We apply the same set of fixed effects as the main specification. Overall, we find no relationship between being on the late sunset side of the time zone boundary and R&D spending. This suggests that while aggregate declines in workforce sleep may impact innovation output, there is no effect on innovation *input*. This result has implications for innovative efficiency. It suggests that if a firm has a workforce with poor sleep, for each dollar of R&D investment, the firm will see less innovation output. This highlights the value of sleep, following the previous subsection.

Additionally, we test for differences among other firm fundamentals which serve as our primary covariates, including ln*(Total Assets)*, *ln (Employees)*, *Leverage*, *Market-to-Book*, *ROA*, and *Cash-to-Asset*.[16] Across all specifications, there is no statistically significant effect on any of the tested firm characteristics. This test aids in ruling out potential endogeneity issues due to potentially omitted variable bias, as the *LS* measure is unrelated to firm characteristics that may serve to confound the main results.

6.2.2. Alternative thresholds

To rule out concerns that the main results may arise out of chance, we perform a series of placebo tests that apply the main specification on alternative cutoffs around time zone boundaries. Specifically, we test for possible discontinuities at 150, 100, and 50 miles on either side of the time zone boundaries. We plot the coefficient estimates for *LS* at these alternative thresholds in Fig. 5, and include the actual coefficient estimate from the main specification for comparison.

As Fig. 5 illustrates, all estimates from the placebo thresholds are statistically insignificant and near zero. The only coefficient that is statistically significant is from the actual time zone boundary threshold that we apply in Section 5.1. This test provides evidence suggesting it is highly unlikely that the main results are a product of chance or a random spurious relationship, as the only relevant possible threshold is at exactly the actual time zone boundaries.

6.2.3. Simulations

As an additional test, we utilize a bootstrap-placebo simulation procedure. For this exercise, we randomly assign each firm a distance to the time zone boundary, then re-run the main specification (Table 4, Column 3) using the assigned *placebo-LS* and *placebo-Miles to TZ Border* measures. We repeat this procedure 10,000 times. Notably, this procedure maintains the same set of firm characteristics, the same time-series, and the same latitude, only altering the distance to the time zone boundary. Overall, this allows us to compare the magnitude and significance of the principal estimates to those that would have arisen purely out of chance. We plot the distribution of simulated placebo coefficients in Fig. 6.

Overall, the figure suggests that the estimates we find in in Section 5.1 are significantly larger than those that could have arisen by chance. In fact, across 10,000 simulations, no placebo coefficient is greater than that which we find in the main specification. This provides evidence that the main empirical design is capturing the effect of the time zone boundary, and thus the effect of the sleep discontinuity.

6.2.4. Alternative measures

This subsection reports the effect of a late sunset time (sleep proxy) on a variety of alternative innovation-based measures beyond those we report in the main results of Section 5.1. We first examine two citation-based measures of a firm's innovative output: both total citations on patents applied for and average citations per patent in a given firm-year.

[14] For comparison, Genin et al. (2023) finds that a one-standard deviation in board experiential diversity increases breakthrough patenting by 34 patents. In addition, Sunder et al. (2017) find that having a pilot CEO is associated with an increase of about 32 patents.

[15] We also perform a supplementary analysis whereby we obtain the average county-level sleep duration over the sample period from the ATUS and link it to the firm-year panel. We regress this county level measure on our main innovation output measure and present our results in Table IA.2 in the Internet Appendix. Overall, this analysis suggests that an increase in average county-level sleep by 20 min corresponds to an average increase of about 14 patents per firm, roughly matching the main result from the spatial RDD.

[16] For the additional firm fundamentals, we examine firms with non-missing R&D investment for consistency.

Table 5
Other Firm Characteristics.

	(1) R&D Intensity	(2) ln(Total Assets)	(3) ln(Employees)	(4) Leverage	(5) Market-to-Book	(6) ROA	(7) Cash-to-Asset
LS	−0.035	0.718	−0.020	−0.459	−0.171	0.093	0.020
	(−0.915)	(1.060)	(−0.042)	(−0.880)	(−0.197)	(1.534)	(0.424)
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Latitude FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8229	8229	8187	8155	8228	8229	8170
R-squared	0.178	0.181	0.218	0.076	0.076	0.126	0.135

This table reports the effect of a late sunset time on innovation. In Columns 1–7, the dependent variables are firm characteristics that we apply as covariates in the main design (Section 5.1). The independent variable of interest is *LS*, an indicator variable equal to one if the firm headquarters are located on the late sunset side of a time zone border. Controls include *ln(Total Assets)*, *R&D Intensity*, *ln(Employees)*, *Leverage*, *Market-to-book*, *ROA*, and *Cash-to-asset.* All estimates include *Miles to TZ Border* and *LS* · *Miles to TZ Border. Commuting Zone* indicates whether observations from 20 miles on either side of the time zone boundary are excluded from the analysis. Fixed effects are included where indicated. The spatial RDD bandwidth is 400 miles on either side of the time zone boundary. Key variables are defined in the Appendix. We winsorize all continuous variables at the 99 % level. Standard errors are clustered at the geographic level based on the distance to the time zone boundary. T-statistics are shown in parentheses. ***, **, * denote significance at 1 %, 5 %, and 10 % levels, respectively.

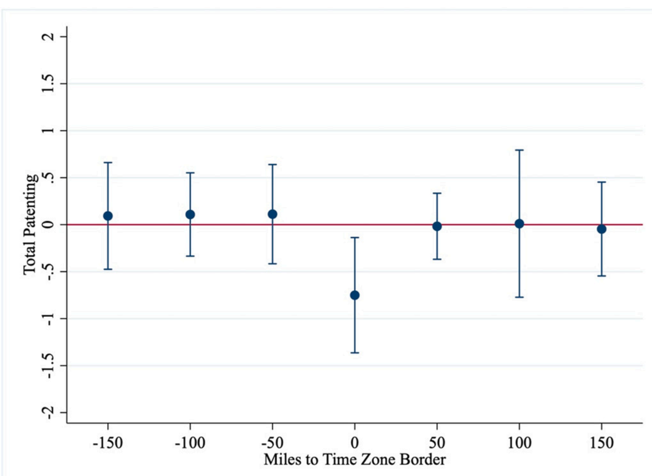

Fig. 5. Placebo Thresholds. This figure presents coefficient estimates from the primary analysis varying the principal time zone boundary cutoff to act as a placebo test. The x-axis presents the running variable *Miles to TZ Border*, whereby positive values fall on the late sunset side of a time zone boundary and negative values fall on the early sunset side. The y-axis reports coefficient estimates of total patenting (*ln(1 + Patents)*) at a variety of alternative cutoffs relative to the time zone boundary. We report the coefficient estimates alongside 95 % confidence intervals.

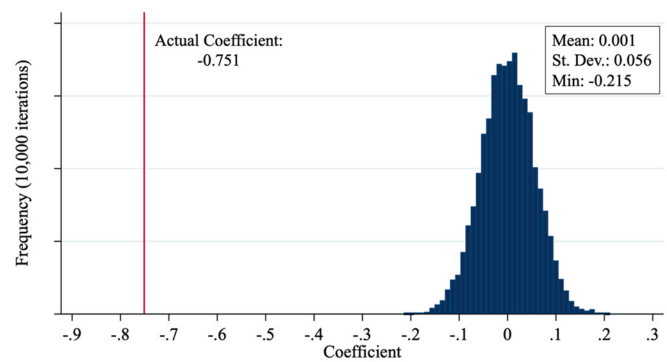

Fig. 6. Pseudo-Boundary Simulation Exercise. This figure presents regressions that follow Column 3 of Table 4 but for counties that are randomly assigned to the late sunset side of a time zone boundary. For this exercise, we perform 10,000 simulations testing the magnitude of the randomly assigned *LS* estimates. We record the coefficients of the *pseudo-LS* variables and plot them in a histogram, along with the associated summary statistics. We plot the value of the actual coefficient from the main design (Table 4, Column 3) in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

This follows from several studies using citations per patent and citation-based metrics as measures of corporate innovation (Blanco and Wehrheim, 2017; Hall et al., 2005; Li and Wang, 2023). Second, we test the effect of a late sunset time on total *novel* patents and the total citations earned on such patents. In this case, we define novelty using the textual dissimilarity measure of Kuhn et al. (2020) and applying the same classification procedure as Genin et al. (2023).[17] We utilize the same identification strategy and specification as the main design and report our results in Internet Appendix Table IA.3.

Across all models, being on the late sunset side of the time zone boundary is associated with statistically significant declines in citations, citations per patent, novel patents, and citations on novel patents. This suggests our results are robust to an array of alternative measures.

6.2.5. *Poisson specification*

Since patent data tends to be right skewed, in our baseline analysis we follow the common practice in the literature and take the log of one plus the total number of patents. Given recent developments in the literature that suggests this approach may induce bias, we estimate Poisson regression models on all of our main results that examine patent count (Cohn et al., 2022). For the baseline spatial RDD, we report these results in Internet Appendix Table IA.4. Overall, the results are nearly unchanged, with the coefficient estimates of interest remaining negative and statistically significant.

6.2.6. *Multilevel mixed-effects specification*

As an additional robustness test, we run a multi-level mixed effects specification. This allows us to account for the hierarchical structure of the data which may not be adequately captured using the OLS specification of the main design. We present our results using this alternative model in Internet Appendix Table IA.5. Overall, the result remains statistically significant and at a similar magnitude as the main design. This suggests that the structure of the data is not likely to be confounding the main results.

6.2.7. *Alternative bandwidths and polynomials*

This subsection re-runs the baseline analysis applying a number of

[17] We classify highly novel patents as those with a textual dissimilarity score in the top ten percentile distribution in a given industry-year following Genin et al. (2023).

alternative bandwidths and a 2nd degree global polynomial to illustrate robustness to alternative specifications. We report these results in Internet Appendix Table IA.6. We estimate the results using bandwidths between 100 and 350 miles in Columns 1–6. In Column 7, we estimate the results using a second-degree global polynomial.[18] Overall, the results indicate that the estimates are robust to a variety of bandwidths and using a higher order polynomial. We do not include higher order polynomials as these are less appropriate for regression discontinuity designs (Gelman and Imbens, 2019).

6.2.8. Firm density

It may be the case that the density of firms is greater on one side of the time zone boundary due to selection. In this case, it may be possible that certain firms that have a more efficient level of innovation choose to relocate to the early side of the time zone boundary, while firms that have a less efficient level of innovation choose to relocate to the late sunset side. This alternative hypothesis suggests firm managers take into account local sunset times and positions around time zone boundaries when deciding where to locate a firm. We test for this alternate hypothesis in Internet Appendix Table IA.7. We aggregate the total number of firms by industry and county for each year in the sample. The coefficients on *LS* not statistically significant, suggesting that firms do not "bunch" on one side of the time zone boundary. This result in is line with previous studies applying the exogeneity of the distribution of time zone boundaries (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019).

6.2.9. Industry agglomeration

This subsection tests for discontinuities in the distribution of industries across time zone boundaries. It may be the case that certain industries intentionally have a preference for one side of the time zone boundary, and those industries have higher levels of innovation. While we account for industry as fixed-effects in our main specification, this still could be a confounding concern relating to selection by industries. We test this alternative hypothesis in Internet Appendix Table IA.8. Overall, we find no clear trends in industry agglomeration on either side of the time zone boundary.[19]

6.2.10. Aggregated county-level specifications

In this subsection, we aggregate all patenting, whether from public or private firms, at the county-level, and re-run our main specification on this alternative sample. While this specification does not account for industry or other firm fundamentals, it may alleviate empirical concerns that the sample of public firms may bias our results due to selection. We present results from this analysis in Table IA.9 in the Internet Appendix.[20] Across all specifications, the results remain statistically significant and negative, suggesting our main results our robust to this alternative sample.

6.2.11. Additional controls

While the baseline specification includes a wide set of firm-level controls and state × year, and industry × year, and latitude fixed effects, it may be the case that there are some local demographic or geographic trends that may explain some of the effect on innovation. In this section, and to account for possible omitted variable bias, we widen the set of controls to account for local demographic characteristics, such as housing prices, population, income, the unemployment rate, racial demographics, age, and gender. We present this analysis in Internet Appendix Table IA.10. Overall, the coefficient estimates are mostly unchanged, suggesting our results are robust to the inclusion of a wider set of controls.

6.3. Alternative specification

6.3.1. Empirical design

In this section, we introduce a novel identification strategy, and we exploit a unique setting to further supplement the initial analysis. In 2006, Indiana began observing daylight savings time on the eastern side of the time zone boundary that divides the state. This marked the first time in the state's history in which all counties observe daylight savings time. In practice, this meant that before 2006, during daylight savings time, the time zone boundary that divided the state functionally disappeared. After 2006, the boundary was a permanent fixture throughout the year. This means that during DST time, after 2006, Indianans experience a later sunset time than years prior, providing exogenous variation in the main instrument. We illustrate this design in Fig. 7, whereby the "treated" side of Indiana receives more natural light in the evening following the DST adoption. More formally, for the primary triple difference analysis in Table 6, we apply the following specification:

$$\begin{aligned} \mathrm{Y}_{i,t} = & \alpha_0 + \alpha_1(\mathrm{LS} \times \mathrm{IN} \times \mathrm{Post})_{c,t} + \alpha_2(\mathrm{LS} \times \mathrm{Post})_{c,t} + \alpha_3(\mathrm{IN} \times \mathrm{Post})_{c,t} \\ & + \alpha_4 \mathrm{X}_{i,t} + \alpha_5 \mathrm{W}_{i,t} + \alpha_6 \mathrm{F}_i + \varepsilon_{i,t,c} \end{aligned} \tag{2}$$

where $Y_{i,t}$ is an outcome of interest, *LS* is an indicator for a county being on the late sunset side of a time zone boundary, and *IN* is an indicator for a county being within the state of Indiana. *Post* is an indicator equal to one for years following Indiana's DST adoption. $X_{i,t}$ is a vector of control variables. $W_{i,t}$ and F_i are vectors of both industry × year and firm fixed effects.

6.3.2. Daylight savings time and sleep declines

To validate this identification strategy, we first test for declines in sleep during DST resulting from the exogenous variation in the instrument. If the delay in sunset time is a valid instrument for sleep loss, we should observe significant declines in sleep duration following 2006 only during DST, with no effect not during regular time.

We provide these results in Table IA.11 in the Internet Appendix. Consistent with our hypothesis, following 2006, individuals on the late sunset side of the time zone boundary in Indiana see a 53.9-min decrease in sleep during daylight savings time. Consistent with expectations, there is no effect during regular time. Given DST lasts from March to November, this equates to a significant average yearly decline for the average Indiana citizen. Overall, this subsection illustrates the validity of the instrument for the triple-difference empirical test. Following these results, we test for declines in innovation following DST adoption in Indiana in the next subsection.

6.3.3. Daylight savings time and innovation

Given the exogenous decline in sleep in the previous subsection, this subsection tests for declines in innovation in the treated areas of Indiana. We illustrate these results in Table 6.

The coefficient of interest is *LS* × *IN* × *Post*. We apply the same set of firm-level controls as the baseline specification in Table 6. In addition, we apply both firm and industry × year fixed effects, thus comparing within-firm variation in innovation before and after the DST adoption. For additional robustness, we apply several bandwidths.[21] Overall, the coefficients on *LS* × *IN* × *Post* are statistically significant and negative in all models, and at similar magnitudes as the baseline design.

[18] In order to maximize the number of observations that fall within tighter bandwidths, we estimate these specifications absent the *Commuting Zone*.

[19] There exists a marginally significant effect for the transportation industry, but this effect is not likely due to systematic trends in industry preference.

[20] For this specification, data on patenting activity comes from PatentsView. To minimize measurement error, we remove counties with a population of <500 people.

[21] Also for additional robustness, we apply the same identification strategy but with a Poisson specification. Our results remain robust to this change. We report these results in Internet Appendix Table IA.12.

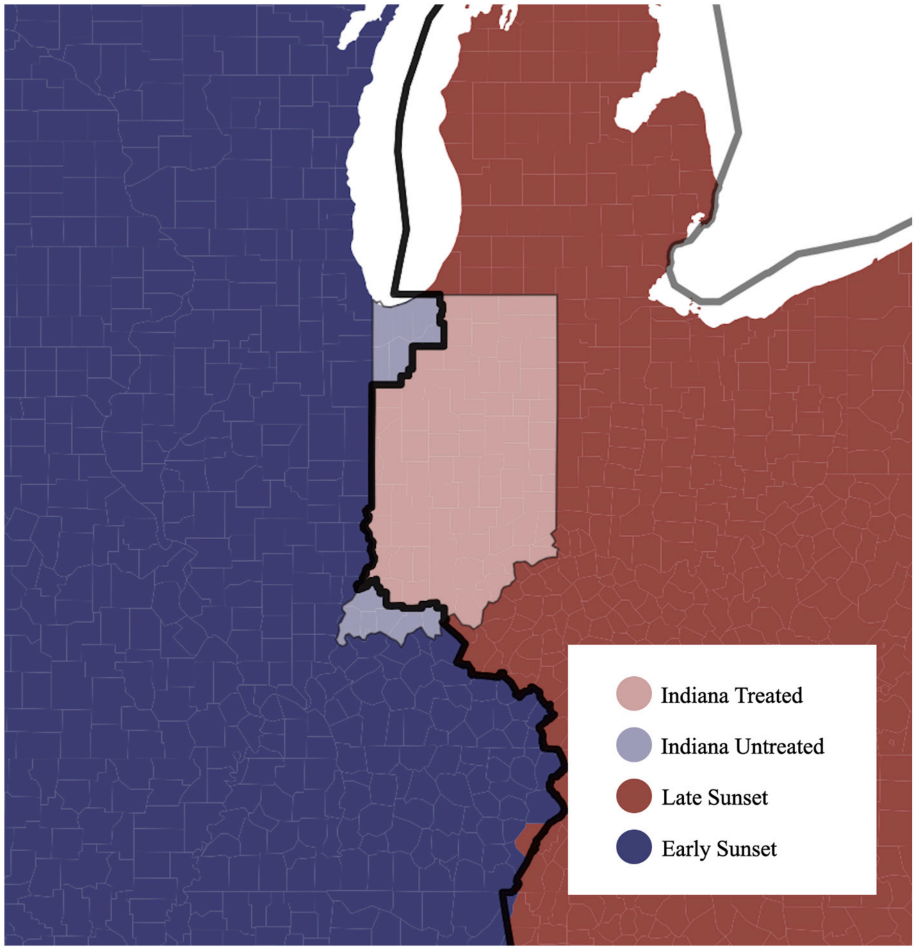

Fig. 7. Indiana and Daylight Savings Time. This figure illustrates the geography of Indiana relative to the time zone boundary. Effective April 2, 2006, the treated area of the state of Indiana began observing daylight savings time, resulting in a later sunset time for most of the year.

We also explore the possibility that the results may be due to pre-existing trends in innovation or due to spurious correlation between the DST adoption and patenting. We perform a parallel trends analysis by augmenting the specification in Table 6, column 4 using yearly indicator variables instead of the *Post* variable in the respective interaction terms. In Fig. 8, we plot the coefficients from the triple interaction term for each year in our sample, capturing corporate innovation trends before, during, and after the adoption of DST in Indiana. First, there is no clear trend in the coefficient of the main interaction before or during the adoption of DST in Indiana. Second, the results become statistically significant only in the years following the DST adoption, suggesting that the adoption of DST has a causal impact on firm innovation.

In summary, the results from the analysis in Table 6 further suggests that aggregate sleep declines have a distinct and economically significant effect on firm innovation using a distinct identification strategy than the baseline analysis.

7. Post-hoc analyses

In this section, we explore patent-level and firm-level heterogeneity in the effects of sleep on innovation output that aids in understanding our findings and phenomenon. First, we test whether more creative, breakthrough patents see larger declines in output from sleep than consolidating patents. If the results are stronger for more breakthrough innovation, then this is indicative of creativity being a key factor in the link between sleep and corporate innovation. Second, we test whether firms engaged in more creative, sophisticated work, namely the output of research, see large declines in productivity as a function of the aggregate declines in sleep. This may suggest that the effect of sleep on productivity may also be a supplementary component in explaining the main results.

To examine this. we apply several additional variables. From the patent data, we use two primary measures to measure novel, valuable innovation: *destabilizing* and *consolidating* patenting. For the former, we identify a firm's innovation using the CD Index, as developed in Funk and Owen-Smith (2017). This measure of "path-breaking" innovation has been used in a variety of studies to identify radical innovation (Agha et al., 2022; Azoulay et al., 2019; Biggi et al., 2022; Kaltenberg et al., 2023). The CD Index measures the extent a focal patent increases or decreases the use of prior technological knowledge.[22] We define a patent as *destabilizing* for positive CD Index values and *consolidating* for negative CD Index values. In order to capture firm productivity, we define *TFP* as revenue-based productivity. We construct this variable following the

[22] This follows the functional form:

$$CD_t = \frac{1}{n_t}\sum_{i=1}^{n}\frac{-2f_{it}b_{it} + f_{it}}{w_{it}}, w_{it} > 0$$

Where $i = (i_1, i_2, \ldots, i_n)$ is a vector containing the future patent that cite the focal patent of interest at time t; w_{it} indexes the matrix W using weights for patent i at time t; n_t represent the number of forward citations that the focal patent as well as its prior ort receives. Lastly, f_{it} is a binary variable equaling 1 if i cites the focal patent and 0 otherwise while b_{it} is a binary variable that equals 1 if i cites any of the focal patent's predecessors and 0 otherwise. By construction, the CD_t value is bounded between −1 and 1.

Table 6
Innovation Following DST Adoption.

	(1)	(2)	(3)	(4)
DV: ln(1 + Patents)				
LS × IN × Post	−0.663***	−0.783***	−0.950**	−1.084**
	(−3.133)	(−3.482)	(−2.450)	(−2.931)
LS × Post	−0.004	−0.007	0.135	0.126
	(−0.054)	(−0.100)	(0.804)	(0.725)
IN × Post	0.301***	0.421***	0.364***	0.466***
	(3.119)	(4.217)	(3.279)	(3.033)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Commuting Zone	No	Yes	No	Yes
Bandwidth (miles)	400	400	100	100
Observations	6989	6897	761	709
R-squared	0.898	0.897	0.946	0.948

This table illustrates the impact of the adoption of DST in Indiana on innovation outcomes. The dependent variable is the logarithm of one plus the number of patents. The independent variable of interest is the interaction of *LS*, *IN*, and *Post*. *LS* is an indicator equal to one if the firm headquarters lies on the late sunset side of the time zone boundary. *IN* is an indicator equal to one if the firm is headquartered in the state of Indiana. *Post* is an indicator equal to one following the adoption of DST by Indiana. Controls include *ln(Total Assets)*, *R&D Intensity*, *ln(Employees)*, *Leverage*, *Market-to-book*, *ROA*, and *Cash-to-asset.* All estimates include *Miles to TZ Border* and *LS · Miles to TZ Border*. *Commuting Zone* indicates whether observations from 20 miles on either side of the time zone boundary are excluded from the analysis. Fixed effects are included where indicated. Key variables are defined in the Appendix. We winsorize all continuous variables at the 99 % level. Standard errors are clustered at the geographic level based on the distance to the time zone boundary. T-statistics are shown in parentheses. ***, **, * denote significance at 1 %, 5 %, and 10 % levels, respectively.

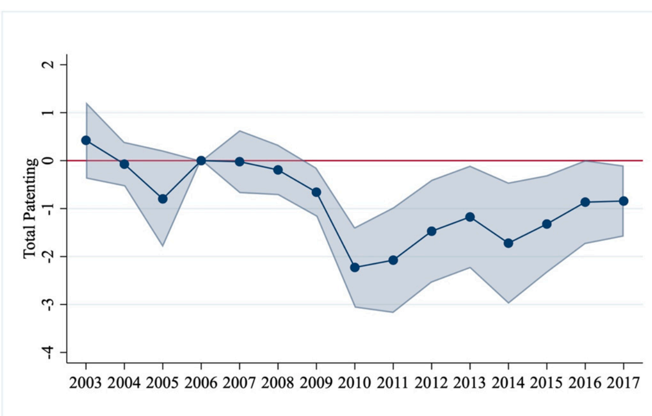

Fig. 8. Innovation Following DST Adoption. This figure provides the dynamics of the triple difference estimates examining the years before and after the inception of DST in Indiana in 2006. The figure plots the dynamic coefficient estimates for total patenting (*ln(1 + Patents)*). The year of the primary DST shift serves as the base year. The figure includes the estimated coefficients and the associated 95 % confidence interval.

measure of Olley and Pakes (1996) using the procedure in Imrohoroğlu and Tüzel (2014).

7.1. Breakthrough innovation

This subsection examines the differential effects of aggregate declines in sleep on path-breaking, breakthrough innovation, which is broadly defined as innovation which sets new paths for future technology. This kind of innovation is highly valuable for long-term value creation not only for the inventing firm but also for society at large (Kogan et al., 2017). Given that path-breaking innovation requires firms engage in intense, creative exploration at the technological forefront, we propose that this valuable innovation may be more likely to see significant declines due to the creativity losses resulting from insufficient sleep (Manso, 2011).

Table 7 provides the results of our additional analyses. From the patent data, we use two primary measures to measure novel, valuable innovation: *destabilizing* and *consolidating* patenting. For the former, we identify a firm's innovation using the CD Index, as developed in Funk and Owen-Smith (2017). The CD Index measures the extent a focal patent increases or decreases the use of prior technological knowledge.

We report the baseline specification in Column 2 for destabilizing patenting and in Column 4 for consolidating patenting. Overall, we find that aggregate sleep declines have about a 19.1 % higher effect for destabilizing innovation than for consolidating innovation.[23] We also test this at the patent level in Internet Appendix Table IA.13. At the patent level, we find that being on the late sunset side of the time zone boundary reduces the probability of an individual patent being *destabilizing* by about 13.3 %. Overall, these results suggest that more creative, exploratory innovation is differentially impacted by sleep loss, suggesting that the effects of sleep on creativity may serve as a potential pathway to partially explain the main results. Future research could provide more nuance on different potential mechanisms using our results as a starting point.

7.2. Productivity

This subsection tests for firm-level differences in productivity that result from differences in aggregate sleep. Sleep is documented to reduce productivity, particularly for more sophisticated tasks (Edmondson et al., 2001). If sleep reduces productivity on innovative work, then we should observe the highest productivity declines for the most research and development-oriented firms. In other words, following the literature on sleep, we should observe the highest declines in productivity for the firms who most rely on non-routine and complex thinking (Edmondson et al., 2001). In this way, we can explore how the effect of sleep on firm-level productivity may explain the main results.

Table 8 provides the results of our additional tests. We apply the measure of total factor productivity from Imrohoroğlu and Tüzel (2014), which we denote as *TFP*. In Table 8, we first divide the sample by patent producing and non-patent producing firms in columns 1 and 2.[24] In this analysis, we find that the effects of sleep on productivity concentrate entirely within patenting firms. This result suggests firms in non-research-oriented industries, such as service industries, likely see far less declines in productivity as a result of sleep, if any. Additionally, columns 3 and 4 divide the sample of patent producing firms by R&D intensity.[25] In this sample, we observe a similar dynamic. Firms with a high focus on research see the majority of the decline in productivity. Overall, this is consistent with the effects of sleep on productivity, and suggests this relationship likely serves as a potential mechanism that explains the relationship between sleep and reductions in innovation.

8. Discussion

Considering the strong link between human capital and innovation, it is essential to understand the factors that affect human capital effectiveness, with sleep being a primary factor. Given the crucial role of sleep in enhancing individual creativity and effectiveness, the overall

[23] We calculate this figure using the proportional difference in the declines associated with the coefficients in columns 2 and 5 of Table 5.

[24] Given we divide the sample, we perform the analysis without the *Commuting Zone* to maximize the available statistical power.

[25] We divide the sample by within industry-year median values of *R&D Intensity*.

Table 7
Path-Breaking Innovation.

	(1)	(2)	(3)	(4)
	ln(1 + Destabilizing)	ln(1 + Destabilizing)	ln(1 + Consolidating)	ln(1+ Consolidating)
LS	−0.902***	−0.822***	−0.853***	−0.653***
	(−3.561)	(−2.941)	(−3.388)	(−3.205)
Controls	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Latitude FE	Yes	Yes	Yes	Yes
Commuting Zone	No	Yes	No	Yes
Observations	7141	7037	7141	7037
R-squared	0.708	0.707	0.613	0.615

This table reports the effect of a late sunset time on path-breaking innovation. In Columns 1–2, the dependent variable is the logarithm of one plus the number of destabilizing patent counts. In Columns 3–4, the dependent variable is the logarithm of one plus the number of consolidating patent counts. The independent variable of interest is *LS*, an indicator variable equal to one if the firm headquarters are located on the late sunset side of a time zone border. Controls include *ln(Total Assets)*, *R&D Intensity*, *ln(Employees)*, *Leverage*, *Market-to-book*, *ROA*, and *Cash-to-asset.* All estimates include *Miles to TZ Border* and *LS · Miles to TZ Border. Commuting Zone* indicates whether observations from 20 miles on either side of the time zone boundary are excluded from the analysis. Fixed effects are included where indicated. The spatial RDD bandwidth is 400 miles on either side of the time zone boundary. Key variables are defined in the Appendix. We winsorize all continuous variables at the 99 % level. Standard errors are clustered at the geographic level based on the distance to the time zone boundary. T-statistics are shown in parentheses. ***, **, * denote significance at 1 %, 5 %, and 10 % levels, respectively.

Table 8
Productivity (TFP) at R&D Intensive Firms.

	(1)	(2)	(3)	(4)
Dependent Variable: TFP				
	Patenting Firms	Non-Patenting Firms	High Research Intensity	Low Research Intensity
LS	−0.262***	0.091	−0.487**	−0.252
	(−2.699)	(1.064)	(−2.092)	(−1.637)
Controls	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Latitude FE	Yes	Yes	Yes	Yes
Observations	5241	8115	1772	2681
R-squared	0.634	0.563	0.651	0.687

This table reports the effect of a late sunset time on total factor productivity. The dependent variable is *TFP*, a measure of revenue based productivity constructed based on the methodology of Olley and Pakes (1996) using the procedure in Imrohoroğlu and Tüzel (2014). The independent variable of interest is *LS*, an indicator variable equal to one if the firm headquarters are located on the late sunset side of a time zone border. A firm is considered to have a high research intensity if the *R&D Intensity* ratio is in the upper median of its industry (3-digit SIC), and low research intensity otherwise. Controls include *ln(Total Assets)*, *R&D Intensity*, *ln(Employees)*, *Leverage*, *Market-to-book*, *ROA*, and *Cash-to-asset.* All estimates include *Miles to TZ Border* and *LS · Miles to TZ Border.* Fixed effects are included where indicated. The spatial RDD bandwidth is 400 miles on either side of the time zone boundary. Key variables are defined in the Appendix. We winsorize all continuous variables at the 99 % level. Standard errors are clustered at the geographic level based on the distance to the time zone boundary. T-statistics are shown in parentheses. ***, **, * denote significance at 1 %, 5 %, and 10 % levels, respectively.

sleep quality of a workforce significantly influences a corporation's innovative output. In this study, we build on recent efforts in developing an integrative constraint theory of innovation (Acar et al., 2019) and argue that sleep deficiency is a particularly important cognitive constraint that hinders the innovative process. Specifically, a lack of sleep limits the number of ideas generated during the innovation process. Since idea generation is the starting point for any corporate innovation, any constraint on this initial step reduces the number of corporate innovations produced.

Furthermore, we argue that sleep deficiency constrains the subsequent steps in the innovation process, particularly the idea elaboration phase and the iterative loop between elaboration and generation. This process is crucial for further development of the ideas into innovations for two reasons. First, it facilitates a deeper understanding of various nuances and problems, enabling the discovery of non-obvious solutions. Second, ideas that often appear as bad ideas initially due to their paradigm-shifting nature, may be ignored or discarded early on. Sleep deficiency reduces the frequency with which scientists engage in this iterative process, diminishing their likelihood of pushing ideas through. It also limits the generation of non-obvious solutions.

We measure an exogenous discontinuity in aggregate workforce sleep around time zone boundaries and use this natural experiment to understand how sleep influences innovative output. This spatial regression discontinuity design is valid and powerful because, although clock time changes significantly across time zone borders, the actual amount of sunlight remains nearly identical on both sides, making it a strong exogenous shock. This discrepancy between clock time and biological time results in sleep deficiency for those on the late side of the time zone border. By leveraging this natural experiment, we can test our hypothesis on the effects of sleep deficiency on corporate innovation. We compare firms on each side of the border while controlling for other firm characteristics.

Our results show that a moderate decline in a workforce's average sleep, by about half an hour, can significantly impact a firm's patent output. Follow-up tests indicate that this effect is even more pronounced for creative, destabilizing patents. Moreover, the negative impact of sleep deficiency on productivity is most evident at firms focused on research and innovation. This aligns with the idea that insufficient sleep affects complex and creative tasks more than routine ones (Weinberger et al., 2018; Williamson et al., 2019). Our findings are robust across various tests, including a triple DiD design, alternative estimation strategies, different measures, and the exclusion of alternative explanations.

8.1. Contributions

Our study makes several contributions to the literature. First, we contribute to recent efforts in developing a constraints theory of innovation (Acar et al., 2019) by identifying sleep (or the lack thereof) as a crucial constraint. Prior research has highlighted various determinants, such as institutions (Donges et al., 2023), board networks (Chang and Wu, 2021), government spending (Kong, 2020), patent laws (Moser, 2005), labor laws (Acharya et al., 2013), competition (Aghion et al., 2005), failure, and the ability to tolerate setbacks (Manso, 2011), along with a broad range of finance-related antecedents (Kerr and Nanda, 2015).

However, our investigation aligns with Cinnirella and Streb (2017) by examining human capital and its influencing factors, particularly sleep. Specifically, Acar et al. (2019) have issued a call for more studies on neurological constraints affecting human capital and innovation. By focusing on sleep, a surprisingly underexplored constraint despite its well-documented negative effects in other fields, we address this call. This study also indirectly enhances our understanding of the social element as a constraint. While most literature focuses on the social context within a firm or team, our results suggest that the external social environment is equally important. Relatedly, the setup of our natural experiment also introduces microgeography (Roche, 2020) as a novel constraint, expanding the scope of factors considered in innovation studies.

Second, we contribute to a multilevel theory of innovation by linking creativity to corporate innovation through sleep. Anderson et al. (2014) found that multilevel research on creativity and innovation is scarce. Our study adds to the behavioral and micro-foundations literature by investigating how individual-level factors affect corporate-level innovation in various ways. Our results indicate that even a small amount of sleep deprivation can have significant effects on corporate innovation. Specifically, a lack of sleep leads to fewer innovations. Follow-up tests also show that a lack of sleep reduces the number of citations these patents ultimately receive. Previous studies often ignored these lower-level antecedents due to limited data, relying instead on small-scale experiments conducted over short periods. While such experiments are useful for studying creativity, they are less ideal for corporate innovation, which often takes years to materialize.

Third, while prior studies have explored other geographical factors, such as microgeography (Roche, 2020), collocation (Jaffe et al., 1993), clusters and their dynamics (Kim et al., 2022), and local infrastructure (Agrawal et al., 2017), our empirical strategy uses time discontinuities at the US time borders as a measure for sleep insufficiency (Giuntella and Mazzonna, 2019). Unlike most other geographical antecedents, time zones are an arbitrarily imposed social construct that is non-physical in nature, unlike roads and other geographical infrastructure. Our identification implies that the location relative to a time border significantly affects corporate innovation. Therefore, time zone borders may be an important factor to consider during strategic location decisions.

Lastly, we also make an empirical contribution. There is a lack of intervention studies in the creativity – innovation literature that allow for causal inference. Although our strategy is not perfect, we believe that our empirical approach allows us to come a little closer to causality. True causality is not possible as we cannot conduct randomized large-scale experiments, but our spatial RDD and triple DiD design is a strong attempt to get at causality.

8.2. Policy implications

Our study has several policy implications that apply to firms that engage in innovative work. First, our results imply firms may benefit by investing in flexible work schedules. Firms can implement flexible work schedules that allow employees to better manage their sleep. By offering options such as flexible workday start and end times, remote work opportunities, and compressed workweeks, companies can help employees maintain healthier sleep patterns, and by extension the degree of innovativeness (Beugelsdijk, 2008). Flexible work policies that allow employees to adjust their schedule to fit their own natural circadian rhythms have been shown to increase sleep for employees, as well as general satisfaction (Bloom et al., 2015; Pierce and Newstrom, 1983). Flexible work arrangements have also been shown to increase sleep among employees (Geiger-Brown et al., 2011; Giuntella and Mazzonna, 2019).

Second, firms may benefit by implementing sleep health programs. Companies could invest in sleep health programs that educate employees on the importance of sleep and provide resources for improving sleep quality. This could include workshops, access to sleep health professionals or sleep medicine, and creating rest areas within the workplace for short naps or relaxation. These initial investments could prove to be particularly beneficial given the correlation between destabilizing innovation and its value (Kogan et al., 2017).

Third, firms could monitor and address sleep deficiency concerns. Implementing policies that encourage regular sleep, such as setting limits on late-night work and ensuring that workloads are manageable, can help mitigate the negative effects of sleep deprivation on innovation and productivity. For example, companies could prohibit employees logging into work accounts after certain times to keep productivity and creativity high.

Fourth and finally, the implications of our findings could also influence the location decisions of large corporations and where to locate their R&D centers. The importance of geographical location on innovation is well established in the literature (Alcácer and Chung, 2014; Audretsch and Feldman, 1996). This literature, however, tends to focus on the benefits of industry agglomeration (Alcácer and Chung, 2014; Alcácer and Zhao, 2012) and its dynamics (Kim et al., 2022; Kim and Shaver, 2021) or the urban layout and planning (Roche et al., 2024). These results suggest that boards and other decision makers should also account for time zone when making location decisions as the decision could materially impact their corporate innovation.

8.3. Limitations and future research

This study has a number of caveats and limitations for interpreting the main results, which also provide avenues of research for future studies. One principal limitation is empirical: little data on individual sleep health exists, and no data exists linking personal sleep health individual-to-individual to their innovative output. As such, while we do not observe the sleep durations of specific patent authors, we are able to empirically proxy for the declines in the level of sleep by examining survey data on sleep durations of employees and engineers in the same county, coupled with our identification strategy which leverages time zone boundaries. Future research may benefit by collecting sleep data on patent authors or innovative workers to better measure the effect of sleep health at a more granular level. This research could also examine how other elements of human behavior, such as personality traits, interact with sleep health to influence levels of creativity and innovative thinking.

Additionally, while we note that flexible work schedules are shown to improve employee sleep health, we do not have data on firm scheduling policy. As such, our inference is only theoretical. Future research could benefit from examining the relationships between flexible schedules, innovative output, and creative work. This research may also formally test the effect of sleep as a mediating factor in the relationship between scheduling and innovation. Research in this area may be especially noteworthy due to the recent rise of remote work, and thus flexible scheduling, which has reshaped how employees sleep, work, and innovate.

9. Conclusion

Given the importance of sleep for the creativity and effectiveness of individual workers, the aggregate sleep of a workforce can have a major impact on a corporation's innovative output. Given the association between human capital and innovation, it is critical to understand the determinants of the effectiveness of human capital, of which sleep is a first-order consideration. In this study, we find empirical evidence on the benefits of sleep for corporate innovation. This evidence is entirely consistent with the experimentally documented effects of sleep: sleep reduces creativity and productivity, which serve as two critical inputs to innovative thinking. Overall, this study offers insight into how fundamental elements of the health of a workforce can shape corporate innovation.

CRediT authorship contribution statement

Gianni De Bruyn: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Paul G. Freed:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2025.105191.

Data availability

The authors do not have permission to share data.

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